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Detection of emotions in Parkinson's disease using higher order spectral features from brain's electrical activity

R. Yuvaraj [a,*], M. Murugappan [a], Norlinah Mohamed Ibrahim [b], Kenneth Sundaraj [a], Mohd Iqbal Omar [a], Khairiyah Mohamad [b], R. Palaniappan [c]

[a] School of Mechatronic Engineering, University Malaysia Perlis (UniMAP), Arau, Malaysia
[b] Neurology Unit, Department of Medicine, UKM Medical Center, Kuala Lumpur, Malaysia
[c] Faculty of Science and Engineering, University of Wolverhampton, Telford, UK

ABSTRACT

Objective: Non-motor symptoms in Parkinson's disease (PD) involving cognition and emotion have been progressively receiving more attention in recent times. Electroencephalogram (EEG) signals, being an activity of central nervous system, can reflect the underlying true emotional state of a person. This paper presents a computational framework for classifying PD patients compared to healthy controls (HC) using emotional information from the brain's electrical activity.

Approach: Emotional EEG data were obtained from 20 PD patients and 20 healthy age-, gender- and education level-matched controls by inducing the six basic emotions of happiness, sadness, fear, anger, surprise and disgust using multimodal (audio and visual) stimuli. In addition, participants were asked to report their subjective affect. Because of the nonlinear and dynamic nature of EEG signals, we utilized higher order spectral features (specifically, bispectrum) for analysis. Two different classifiers namely K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) were used to investigate the performance of the HOS based features to classify each of the six emotional states of PD patients compared to HC. Ten-fold cross-validation method was used for testing the reliability of the classifier results.

Main results: From the experimental results with our EEG data set, we found that (a) classification performance of bispectrum features across ALL frequency bands is better than individual frequency bands in both the groups using SVM classifier; (b) higher frequency band plays a more important role in emotion activities than lower frequency band; and (c) PD patients showed emotional impairments compared to HC, as demonstrated by a lower classification performance, particularly for negative emotions (sadness, fear, anger and disgust).

Significance: These results demonstrate the effectiveness of applying EEG features with machine learning techniques to classify the each emotional state difference of PD patients compared to HC, and offer a promising approach for detection of emotional impairments associated with other neurological disorders.

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1. Background

Social communication and the ability to respond to emotional signals are essential for meaningful interpersonal interactions. While Parkinson's disease (PD) has traditionally been defined as a motor system disorder (in the form of tremors, rigidity, and bradykinesia) [1], there is growing evidence of cognitive and social deficits for people associated with this disease [2,3]. Non-motor symptoms, including disruptions in processing of emotional information [4,5] have been found in over 50% of newly diagnosed PD patients [6] and can appear in any stage of disease progression [7]. Interestingly, social cognitive dysfunction has been found before the appearance of motor disturbances in PD [8].

Individuals with PD show impairments in the ability to recognize emotions from facial expressions [9,10], emotional prosody [11,12] and show reduced startle reactivity to highly arousing unpleasant pictures [13,14]. There is sparse event related potential (ERP) evidence that early processing of emotional prosody

* Corresponding author at: School of Mechatronic Engineering, University Malaysia Perlis (UniMAP), Campus UluPauh, Arau 02600, Perlis, Malaysia. Tel.: +60 14 6011990; fax: +60 04 9885167.
E-mail address: yuva2257@gmail.com (R. Yuvaraj).

(mismatch negativity, [15]) and faces (show reduced arousal ratings of highly arousing affective pictures, [16] and early posterior negativity [17]) may be affected in PD. Still there is some controversy about which specific emotions are recognized abnormally in PD. Some researchers report specific impairments in the recognition of fear and sadness [18], whereas others have reported deficits in recognizing anger or disgust [9,10], while still others failed to report emotion recognition deficits [17,19,20]. Altogether, experimental evidence so far supports the view of impairments in emotion processing in PD. Much of the research in this area dealt with behavioral responses (self-ratings) i.e., participants were asked to match, to identify, to judge, or to rate the emotional stimuli and physiological measures of emotional experience (e.g., startle eye blink and ERPs). In addition, all the studies mentioned above used traditional tools (i.e., statistical analysis) for the investigation of emotion-related information processing in PD patients.

In recent years, numerous studies on engineering approaches to automatic emotion recognition using machine learning techniques have been published, although research in this field is relatively new compared to the long history of emotion research in psychology and psychophysiology. In particular, many efforts have been deployed to recognize emotions using facial expressions [21], speech signals [22] and gestures [23] in healthy controls (HC). Though these modalities have been researched widely and have produced better results, they are all susceptible to social masking. Emotions that are not expressed, emotions expressed differently (an angry person may smile) or minor emotional changes that are invisible to the natural eye, cannot be tracked by using these modalities [24]. These limitations lead the way to recognizing emotions through physiological signals (or biosignals) [25]. As physiological signals reflect the inherent activity of the autonomous nervous system (ANS) or the central nervous system (CNS), social masking does not have any influence in recognizing true emotions felt by the person. This approach also provides an opportunity to track minute emotional changes which cannot be perceived visually or by hearing.

Biosignals such as electrocardiogram, galvanic skin response, electromyogram, skin temperature, blood volume pressure, heart rate variability, and body temperature, and respiration rate have been used to evaluate the emotional state of a person. In addition to these biosignals, signals captured from the CNS, such as electroencephalogram (EEG), magnetoencephalogram (MEG), positron emission tomography (PET), and functional magnetic resonance imaging (fMRI) have been proved to provide informative characteristics in response to emotional states. Toward such a more reliable emotion recognition procedure, EEG [26] appears to be less invasive and the one with best time resolution than the other three (MEG, PET, and fMRI). In general, EEG signals have been widely used in order to study brain activity relating to affective responses. Evidence of such activity is reported in the majority of EEG frequency bands such as *theta* (4–8 Hz), *alpha* (8–13 Hz), *beta* (13–30 Hz) and *gamma* (30–49 Hz). For example, frontal midline (Fm) *theta* power modulation is suggested to reflect affective processing during emotional music [27]. The *alpha*-power asymmetry on the prefrontal cortex has been proposed as an index for the discrimination between positively and negatively valenced emotions [28]. *Beta* activity has been associated with emotional arousal modulation [29]. Finally, *gamma* band has been mainly suggested as related to arousal effects [30].

Nonlinear analysis has been applied to many areas such as medicine and biology over the past decade. In particular, the nonlinear analysis method is effectively applied to EEG signals to study the dynamics of the complex underlying behavior [31] and it is well known that the EEG signals exhibit significant non-linear behavior [32]. Non-linear analysis based on chaos theory helps in identifying the apparently irregular behaviors that were present

in the system [33]. Several nonlinear features such as correlation dimension (CD), approximate entropy (AP), largest lyapunov exponent (LLE), higher order spectra (HOS) and Hurst exponent (H) have been used widely [34,35] to characterize the EEG signal. In general, any analysis technique that can detect and quantify some aspect of non-linear mechanisms, may better reflect the dynamics and the characteristics of the EEG signal, and provide more realistic information about the physiological and pathological state of the CNS, the phenomenon of non-linearity and deviations of the signal from [36]. HOS are known to be useful to detect non-linearity and deviations from Gaussian behavior.

Motivated by these, we set out to explore the relation between emotional states and EEG frequency bands in PD patients compared to HC using a set of HOS based parameters as features (specifically, bispectrum). Two different classifiers namely K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) were used to investigate the performance of the HOS based features to classify each of the six emotional states (happiness, sadness, fear, anger, surprise and disgust) of PD patients compared to HC. The remainder of the paper is organized as follows: "Section 2" briefly presents the participants' characteristics, emotion elicitation protocol, and EEG recordings. "Section 3" presents the signal preprocessing, features extracted from the bispectrum and the classifiers used. The results and discussion are presented in "Section 4". Finally, the paper is concluded in the last section.

2. Materials used

2.1. Participants

Twenty PD patients (all right-handed) and 20 HC (all right-handed) matched for age, gender, and education level participated in the study. Parkinson's disease patients were recruited from the clinic Neurology outpatient service of the Hospital University Kebangsaan Malaysia (HUKM) medical center, Kuala Lumpur, Malaysia. All patients had been diagnosed with idiopathic PD by a neurologist and were optimally medicated during the testing session (ON state) with d2-agonist ($n = 18$); carbidopa/L-dopa ($n = 13$), monoamine oxidase B (MAO-B) inhibitor ($n = 7$), catechol-O-methyltransferase (COMT) inhibitor ($n = 5$), amantadine ($n = 5$), or anticholinergics ($n = 3$). The average duration of PD (post-diagnosis) in the group was 5.75 years [standard deviation (SD) = 3.52, range = 1–12 years]. The severity of motor signs in the patient group could be characterized as mild to moderate; all patients fit Hoehn and Yahr stages (H&Y) [37] I–III (Stage I = unilateral disease with mild symptoms, Stage II = bilateral involvement, Stage III = bilateral symptoms with postural and gait disturbances) with a mean Unified Parkinson's Disease Rating Scale (UPDRS) [38] motor score of 17.05 (SD = 3.15). None of the patients had coexisting neurological (e.g., epilepsy) or psychiatric disturbances (e.g., major depression or anxiety, psychotic symptoms) that might independently influence their cognitive functioning.

The HC participants were recruited through the hospital community and/or from relatives of PD patients. Exclusion criteria for controls included any psychiatric or neurological disorder. To exclude dementia or depression, both of the groups scoring 24 or lower on the Mini-Mental State Examination (MMSE) [39] or 18 or higher on the Beck Depression Inventory (BDI) [40] were excluded. Handedness was determined by self-report and confirmed by Edinburgh Handedness Inventory (EHS) [41]. This test consisted of 10 questions asking for the preferred hand for a series of activities (e.g., writing, throwing, using scissors). All participants reported normal or corrected-to-normal vision. Intact hearing was formally established in all participants by administering a pure tone audiometric screening of both ears to ensure acceptable normal

Table 1
Demographic and clinical characteristics of PD patients and HC.

Variable	PD ($n = 20$)	HC ($n = 20$)	Test's value	Statistical result[*]
Age (years)	59.05 ± 5.64	58.10 ± 2.95	$t = 0.667$	$p = 0.509$
Gender	10F/10M	11F/9M	$x^2 = 0.100$	$p = 0.752$
Education (years)	10.45 ± 4.86	11.05 ± 3.34	$t = -0.455$	$p = 0.652$
MMSE (0–30)	26.90 ± 1.51	27.15 ± 1.63	$t = -0.502$	$p = 0.619$
Hoehn and Yahr scale (I/II/III)	2.25 ± 0.63	–	–	–
Motor UPDRS	17.05 ± 3.15	–	–	–
Disease duration (years)	5.75 ± 3.52	–	–	–
BDI (0–21)	5.80 ± 2.87	5.45 ± 2.18	$t = 0.433$	$p = 0.667$
EHS (1–10)	9.55 ± 0.76	9.84 ± 0.72	$t = -0.818$	$p = 0.403$

Note: n, number of participants; PD, Parkinson's disease; HC, healthy controls; M, male; F, female; MMSE, Mini Mental State Examination; UPDRS, Unified Parkinson's Disease Rating Scale; BDI, Beck Depression Inventory; EHS, Edinburg Handedness Inventory. Data presented as mean ± SD.

[*] Difference is significant at the $p < 0.05$ level.

hearing threshold (minimum 30 dB HL at 0.5, 1, 2, and 4 kHz, for the better ear). All participants/caretakers gave informed consent before completing the study, which was ethically approved by the Faculty of Medicine, Institutional Review Board of the HUKM. All participants were paid 50 Malaysian Ringgits for their participation.

Patients and controls were comparable in demographic variables such as age (PD: mean age: 59.05 ± 5.64; HC: mean age: 58.10 ± 2.95; $t(38) = 0.667$, $p = 0.509$), gender distribution (PD: 10 men, HC: 09 men; x^2 (1, $N = 40$) $= 0.100$, $p = 0.752$), and education level (PD: 10.45 ± 4.86 years; HC: 11.05 ± 3.34 years; $t(38) = -0.455$, $p = 0.652$). Table 1 lists the demographic and clinical characteristics of the analyzed PD patients and HC participants. As can be seen from the table, the groups did not significantly differ in mean MMSE scores, mean BDI scores as well as mean EHI scores.

2.2. Stimulus material

Gathering good and meaningful data are essential in any signal processing application. In works related to emotion recognition using physiological signal, acquiring emotional data that corresponds to specific emotional state is challenging, because of the subjective nature of the emotions and cognitive dependence of physiological signals which requires the emotional states have to be elicited internally in the participant. Until now, most studies on emotion recognition in PD have used only facial stimuli, prosodic stimuli, or music stimuli [4,5,42]. In addition, a number of emotion induction techniques using pictures, sounds, music, or multimodal approaches (combination of audio and visual) have been used to elicit target emotions in healthy controls [26,43–46]. Among all of these stimuli modalities researchers have identified that multimodal stimuli induce emotions in the participants more naturally and more effectively compared to other modalities [25,45–47]. In this work, we utilized a multimodal approach to evoke six basic emotions (happiness, sadness, fear, surprise, and disgust) that are universally accepted.

The emotional stimuli we used were taken from different sources, such as the International Affective Picture System (IAPS) database [48], International Affective Digitized Sounds (IADS) [49] database and video clips (e.g., funny animals, wonder activities by humans) collected from various resources on the internet (e.g., YouTube, Facebook, and others) [24]. The elicitation of emotions such as sad, fear, and disgust was attained by using affective pictures from IAPS and sounds from IADS databases. Various psychological and psychophysiological experiments have revealed that these stimuli sets have great potential in the investigation of sad, fear, and disgust emotion [43,50]. In addition, Mikels et al. [51] and Redondo et al. [52] provided a more complete characterization of the categorical structure of the IAPS and IADS stimuli set, with the objective of identifying images and sounds that elicit one discrete emotion more than other emotions. The

IAPS Pictures[1] [*disgust:* valence mean ± SD = 2.43 ± 1.51, arousal mean ± SD = 5.90 ± 2.25; *fear:* valence mean ± SD = 3.80 ± 1.89, arousal mean ± SD = 5.85 ± 2.12; *sadness:* valence mean ± SD = 2.74 ± 1.57, arousal mean ± SD = 5.00 ± 2.08] and IADS sound[2] [*disgust:* valence mean ± SD = 4.00 ± 1.72, arousal mean ± SD = 5.82 ± 1.93; *fear:* valence mean ± SD = 4.00 ± 1.72, arousal mean ± SD = 5.82 ± 1.93; *sadness:* valence mean ± SD = 3.28 ± 1.65, arousal mean ± SD = 6.61 ± 1.89] were selected and combined together according to their arousal and valence values provided in the databases. For example, a negative/high aroused sound was matched with a negative/high aroused image. On the other hand, the emotions happiness, surprise, and anger were elicited using video clips. A pilot study was conducted to identify the video clip that was better able to elicit the target emotion in the participants. Ninety video clips corresponding to happiness, surprise, and anger were displayed to thirty volunteers with a mean age of 26.4 years (ranging from 24 to 45 years). All of the participants were psychology teachers or students at the UKM medical center, Kuala Lumpur. Of these, 30 clips with the highest ratings were chosen for data collection.

2.3. Emotion elicitation protocol

An illustrated representation of the emotion elicitation protocol is shown in Fig. 1(a). As shown in the figure, the protocol had two sessions of three trials each. There was a break of 10–15 min between the sessions. The participants were allowed to relax during the break since the continuous assessment would have been too exhausting. The multimodal stimuli relating to all the six emotional states (happiness, sadness, fear, anger, surprise and disgust) were displayed in each trial in a random order. Each combination of picture and sound was presented for 6 s [22]. To maximize the participants' emotional response, each clip block consisted of six combinations of the same emotional category and lasted for 36 s. In addition, each of the video clips varied from 36 to 45 s in duration, depending on the length of the clip. Neutral images, which can

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[1] The following pictures in the database were used for emotion induction: **Disgust**: 1945, 2352.2, 3000, 3010, 3015, 3030, 3051, 3060, 3061, 3071, 3080, 3110, 3120, 3130, 3140, 3150, 3160, 3250, 3400, 7360, 7361, 7380, 8230, 9040, 9042, 9181, 9290, 9300, 9320, 9330, 9373, 9390, 9405, 9490, 9570, 9830; **Fear**: 1019, 1022, 1030, 1040, 1050, 1051, 1052, 1070, 1080, 1090, 1110, 1111, 1113, 1120, 1200, 1201, 1220, 1230, 1240, 1280, 1274, 1300, 1301, 1302, 1321, 1390, 1930, 1931, 3280, 5970, 5971, 5972, 6370, 9584, 9594, 9592; **Sadness**: 2205, 2271, 2276, 2490, 2520, 2590, 2700, 2800, 2900, 3220, 3230, 3300, 3301, 3350, 6570, 6838, 8010, 9000, 9041, 9050, 9120, 9190, 9210, 9220, 9331, 9410, 9415, 9470, 9520, 9530, 9561, 9611, 9910, 9911, 9920, 9921.

[2] The following sounds in the database were used for emotion induction: **Disgust**: 134, 115, 251, 262, 284, 698, 702, 711, 712, 713, 714, 720, 728, 729, 730, 732, 812, 813; **Fear**: 106, 133, 170, 171, 275, 276, 277, 279, 291, 312, 378, 380, 424, 425, 500, 626, 627, 699, 817; **Sadness**: 115, 150, 260, 261, 278, 280, 285, 286, 290, 293, 295, 310, 311, 368, 403, 420, 422, 501, 600, 625.

(a)

(b)

(c)

(d)
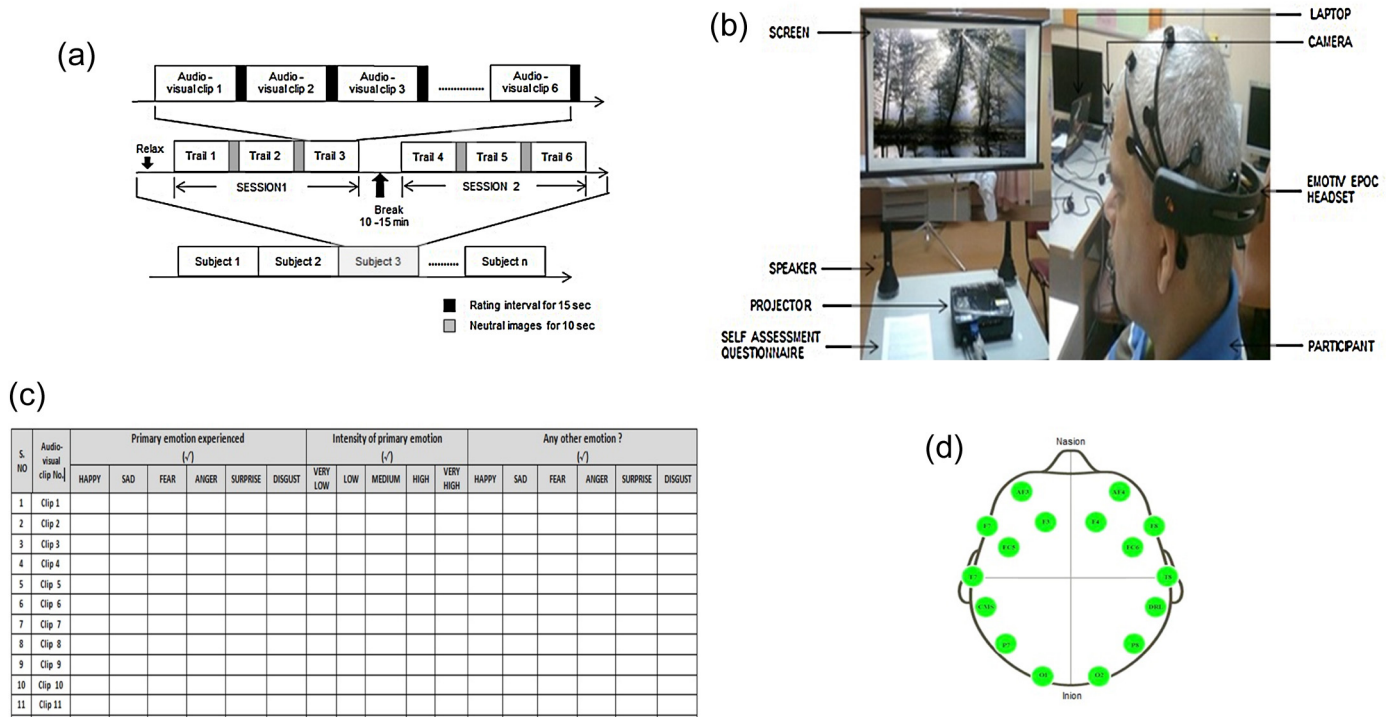
Fig. 1. (a) Schematic representation of the experiment protocol. (b) Experimental setup for emotion assessment using multimodal stimuli. (c) Self-assessment questionnaire. (d) Electrode positions, according to the 10-20 system, of the Emotiv EPOC device used for EEG acquisition.

calm down the participants, were displayed for 10 s at the start of each trial. This would help the participants return to the normal or neutral state away from emotional excitation. Besides, a 15 s rating interval [53] was provided between the clips in which participants answered a five point self-assessment questionnaire. Each session took approximately 30 min.

2.4. Procedure

The purpose of the study was clearly explained to the participants before initiating the experiment. The participants were further requested to relax, minimize their bodily movements (as much as possible, to reduce the appearance of undesired artifacts in the EEG recordings), and concentrate on the emotional stimuli. The self-guided emotion elicitation protocol was then displayed on the screen. The complete experimental set up is shown in Fig. 1(b). At the end of each clip, participants filled a self-assessment questionnaire to state the status of the emotions they felt during the experiment; they were also asked to report the strength of the emotions using a five-point scale according to the degree (1 = very low, 2 = low, 3 = medium, 4 = high, and 5 = very high). These ratings were then used to understand the intensity of the emotional state they experienced. However, despite the intensity levels, all emotional data were taken into considerations. The participants were also allowed to indicate multiple emotions during the experiment. An example of the self-assessment questionnaire is shown in Fig. 1(c).

2.5. EEG recordings

EEG recordings were conducted using the Emotive EPOC 14 channel EEG wireless recording headset (Emotive Systems, Inc., San Francisco, CA) [54]. The electrode scheme was arranged according to the international 10-20 system and included active electrodes at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 positions, referenced to the common mode sense (CMS-left mastoid)/driven right leg (DRL-right mastoid) ground as shown in Fig. 1(d). The

acquired data were digitized using the embedded 16-bit ADC with 128 Hz sampling frequency per channel and sent to the computer via wireless communication, which utilizes a proprietary USB dongle to communicate using the 2.4 GHz band. Sample EEG recordings of PD patient and HC corresponding for six emotional states are given in Fig. 2(a) and (b), respectively.

3. Methodology

3.1. Signal preprocessing

First, the time waves of EEG data were pre-processed using thresholding method to remove eye blinking artifacts, in which data that are found to have amplitudes of more than 80 µV are discarded from the study. Second, a 6th order bandpass Butterworth filter (with forward reverse filtering algorithm) was used to extract the frequency range of 1–49 Hz. The focus was placed upon the five EEG frequency bands, i.e., *delta* (1–4), *theta* (4–8 Hz), *alpha* (8–13 Hz), *beta* (13–30 Hz) and *gamma* (30–49). Third, each channel of the EEG signal was segmented into 6 s epoch without overlapping using time-windows [55]. Finally, features discussed below were computed using each epoch of the EEG data.

3.2. Feature extraction

The main task of the feature extraction stage was to derive the salient features which can map the EEG data into corresponding emotional states. In this work, we have used HOS based features to investigate each of the six emotional states difference of PD patients compared to HC.

3.2.1. Bispectrum computation

Higher order spectra (also known as polyspectra) are the spectral representations of higher order statistics, i.e., moments or cumulants of third and higher orders. In particular, we have studied features related to the third-order statistics of the signal, namely,
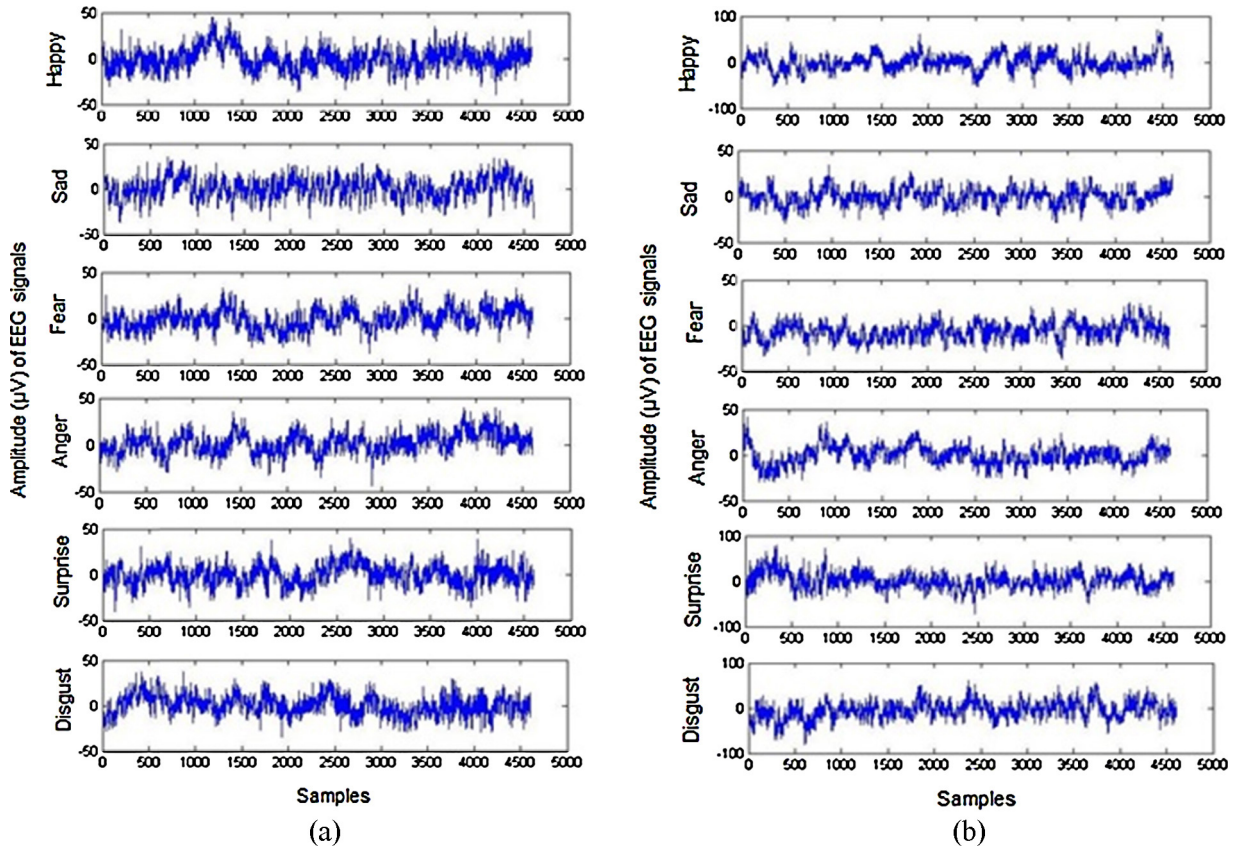
Fig. 2. Sample recording of EEG signals corresponding to six emotions: (a) PD patients and (b) healthy controls.

the bispectrum. The bispectrum is the Fourier transform of the third order correlation of the signal and is given by,

$$B(f_1, f_2) = E[X(f_1)X(f_2)X^*(f_1 + f_2)] \quad (1)$$

where $B(f_1, f_2)$ is the bispectrum in the bifrequency (f_1, f_2), $X(f)$ is the discrete time Fourier transform (FT) of the given signal, * denotes complex conjugate. $X(f)$ is the discrete time Fourier transform for deterministic signals computed with discrete frequency samples using Fast Fourier Transform (FFT) algorithm. The frequency f may be normalized by the Nyquist frequency to be between 0 and 1. The bispectrum given by Eq. (1) is a complex valued function of two frequency variables. It is well known that the FT of a real-valued signal shows conjugate symmetry, and the power spectrum is redundant in the negative frequency region. Likewise, the bispectrum, which is the product of three Fourier coefficients, exhibits symmetry and therefore, was computed in the non-redundant region [56]. Assuming that there is no bispectral aliasing, the bispectrum of a real valued signal is uniquely defined with the triangle $0 \le f_2 \le f_1 \le f_1 + f_2 \le 1$. This is termed as the principal domain or the non-redundant region, denoted as Ω (the triangle region) in Fig. 3. The extracted bispectral based features are:

(i) Mean of bispectral magnitude:

$$M_{avg} = \frac{1}{L} \sum_{\Omega} |B(f_1, f_2)| \quad (2)$$

where L is the number of points within the region.

(ii) Normalized bispectral entropy (BE1)
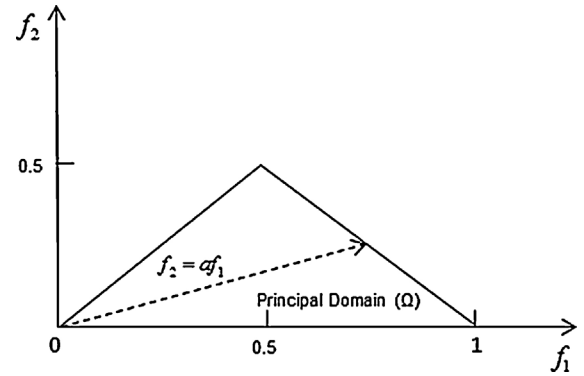
$$P_1 = -\sum_k p_k \log(p_k) \quad (3)$$

Fig. 3. Non-redundant region (Ω) of computation of the bispectrum for real signals.

where $p_k = \frac{|B(f_1, f_2)|}{\sum_{\Omega} |B(f_1, f_2)|}$, Ω = region as in Fig. S1.

(iii) Normalized bispectral squared entropy (BE2):

$$P_2 = -\sum_n q_n \log(q_n) \quad (4)$$

where $q_n = \frac{|B(f_1, f_2)|^2}{\sum_{\Omega} |B(f_1, f_2)|^2}$, Ω = region as in Fig. S1.

The absolute value or magnitude and the square of the magnitude are the L_1 and L_2 norms of the bispectrum. For both of these entropies, normalization was done by the sum of the norm over Ω which is the complete non-redundant bi-frequency region, such that each norm is now similar to a probability distribution function (PDF) with values estimated over the Ω region. These PDFs are

Table 2
Self-assessment classification accuracy (in percentage) for each of six emotional states between PD patients and healthy controls obtained from the confusion matrix.

Emotion	Happy (%)		Sad (%)		Fear (%)		Anger (%)		Surprise (%)		Disgust (%)	
	PD	HC	PD	HC	PD	HC	PD	HC	PD	HC	PD	HC
Happy	**94.33**	**92.50**	0	0	0	0	0	0	5.67	7.60	0	0
Sad	0	0	**75.00**	**84.67**	1.83	0	4.45	2.77	0	0	18.72	12.56
Fear	0	0	2.56	1.49	**80.33**	**77.50**	7.92	12.56	3.48	0	5.71	8.45
Anger	0	0	4.79	0	11.56	15.32	**78.00**	**82.67**	0	0	5.65	2.01
Surprise	12.00	3.33	0	0	0	0	0	0	**88.00**	**96.67**	0	0
Disgust	0	0	24.89	18.42	0	8.12	2.44	6.96	0	0	**72.67**	**66.50**

one-dimensional histograms of these values. They allow entropies, namely P_1 and P_2, to be defined and calculated.

In order to calculate above bispectral features across each frequency band of PD patients and healthy controls, we used epochs of 768 samples with hanning window of 50% overlap corresponding to 6 s at the given sampling rate. These epochs were taken from each record of 1024 NFFT points.

3.3. Classification of emotional states

Twenty participants from each group with six trials and six epochs per channel resulted in a total of 720×14 EEG data samples per emotion, which were processed. All the three HOS features were extracted from these samples. The performance of the emotional feature between PD patients and healthy controls was analyzed using KNN and SVM classifiers across different EEG bands. We also tested other classification techniques such as linear discriminant analysis, probabilistic neural network and Naive Bayes. However, these results are not superior to those obtained with KNN and SVM methods and hence are not reported.

The KNN is a simple data-driven lazy learning algorithm, where an unlabeled point is attributed to the predominant class within the K-nearest labeled points belonging to the training class [57]. Euclidean distance was used as a measure to assess the similarity of testing points. Euclidean distance was calculated using the below formula. In this work, different values of K between 1 and 10 were tested.

$$D_E = (a, b) = \sum_{i=1}^{N} \sqrt{(a_i - b_i)^2} \tag{5}$$

where a and b are the training and testing data, respectively and N is the number of features.

In SVM, a separating hyperplane that maximizes the margin between the input data classes which are viewed in an n-dimensional space (n is the number of features used as inputs) is determined. In general, a larger margin results in a lower generalization error. SVM can be easily adapted to nonlinearly separable data by the use of kernal functions to map the data to a much higher dimensional space where the data becomes more separable [58]. The radial basis function (RBF) kernel and polynomial kernel are most commonly used [59]. With the use of kernels, an explicit transformation of the data to the feature space is not required. In this work, we have used RBF kernel function. The performance parameters of SVM (regularization constant, C and width of the RBF kernal, σ) were obtained by using the grid search approach [60]. To achieve better accuracy, the suitable values of C and σ were given by this algorithm as 108 and 2.434, respectively.

In this work, ten-fold cross validation method was used to test the performance and reliability of the classifiers. During this method, the dataset is divided randomly in ten equal (or approximately equal) subsets and for each fold nine subsets are used for training and one subset for testing. The procedure is repeated ten-times (ten-folds) in order for all subsets to be used as testing data. Classification performance was mainly evaluated through the

classification accuracy (CA) and was computed for each emotional states between PD patients and HC as,

$$\%\text{Accuarcy}_{(PD\,vs\,HC)} = \frac{\text{Number of correctly classified feature vectors}_{Emotion}}{\text{Total number of tested feature vectors}_{Emotion}} \times 100 \tag{6}$$

where *Emotion* refers to one of the six emotional state of PD patients compared to healthy controls (i.e., Happiness$_{(PD\,vs\,HC)}$, Sadness$_{(PD\,vs\,HC)}$, Fear$_{(PD\,vs\,HC)}$, Angry$_{(PD\,vs\,HC)}$, Surprise$_{(PD\,vs\,HC)}$, and Disgust$_{(PD\,vs\,HC)}$) across delta, theta, alpha, beta, gamma EEG frequency bands and ALL (combination of five frequency bands). The overall performance of the classifier was evaluated by taking the average and standard deviation (SD) of the accuracies of ten-folds. Here, the SD of the classification clearly reveals the consistency of the classifier results and the number of classes used for classification here was two.

4. Experimental results and discussion

Table 2 shows the results of the self-assessment phase (in percentage) for each of six emotional states between PD patients and HC. From the table, it can be observed that the subjective response accuracy to emotional stimuli confirmed that the participants were almost able to induce the expected emotions and to investigate the correspondence in EEG responses. It should be also noted that the happiness stimuli were recognized most easily (% average CA = 93.42) whereas, stimuli related to disgust emotion were recognized the worst (% average CA = 69.58).

Table S1(a)–(e) shows the range of three features used for classification obtained from PD patients compared to HC for each of the six emotional states across delta, theta, alpha, beta and gamma frequency bands (see Supplementary file 1). From the tables, it can be observed that there is a decrease in the values of the extracted features from PD patient's EEG signals as compared to the healthy controls during emotion processing. This is due to the dynamic processes underlying the EEG recording that are less complex for PD patients than healthy controls. This confirms to other studies that there will be decrease in brain complexity during emotion processing due to the dysfunction in the neural circuits [10,61,62].

Supplementary tables associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.bspc.2014.07.005.

The statistical significance of all the three features was studied using analysis of variance (ANOVA). The threshold was set to $p = 0.05$ and all the three features showed statistical significance ($p < 0.05$) indicating that the each of the six emotional states of PD patients and HC have significant difference in the feature values, for all cases studied. This would also ensure a higher probability of achieving better classification accuracy in discriminating the emotional states between the groups.

Tables 3a–3f present the classification performance of HOS based features to distinguish each of the six emotional states of PD patient's compared to HC across delta, theta, alpha, beta, gamma

Table 3a
Percentage ± SD of classification of KNN and SVM classifiers with HOS features (M_{avg}, P_1, and P_2) between PD patients and healthy controls emotional state across *delta* (1–4 Hz) frequency band.

Emotion	KNN classifier (%)			SVM classifier (%)		
	PD	HC	AVG	PD	HC	AVG
Happiness	64.84 ± 3.76	75.39 ± 2.58	70.11 ± 3.19	66.49 ± 3.49	76.29 ± 2.01	72.89 ± 2.17
Sadness	61.28 ± 2.13	71.86 ± 3.19	66.57 ± 2.48	64.29 ± 2.57	75.49 ± 3.45	69.89 ± 3.58
Fear	59.20 ± 1.29	65.28 ± 2.30	62.24 ± 3.60	60.49 ± 3.59	70.39 ± 2.59	65.44 ± 3.49
Anger	62.39 ± 3.90	68.44 ± 3.29	65.41 ± 4.04	66.24 ± 4.29	74.12 ± 3.29	70.18 ± 4.56
Surprise	65.38 ± 3.71	73.20 ± 4.83	69.29 ± 3.75	69.72 ± 3.29	75.39 ± 4.22	72.55 ± 3.59
Disgust	60.10 ± 4.49	68.39 ± 5.46	64.24 ± 2.58	62.67 ± 2.49	72.28 ± 2.25	67.47 ± 4.29

Table 3b
Percentage ± SD of classification of KNN and SVM classifiers with HOS features (M_{avg}, P_1, and P_2) between PD patients and healthy controls emotional state across *theta* (4–8 Hz) frequency band.

Emotion	KNN classifier (%)			SVM classifier (%)		
	PD	HC	Average	PD	HC	Average
Happiness	69.22 ± 5.81	71.39 ± 3.65	70.31 ± 4.11	76.54 ± 5.21	77.34 ± 3.10	76.94 ± 4.12
Sadness	62.50 ± 3.45	73.33 ± 3.98	67.92 ± 3.11	67.67 ± 3.96	75.78 ± 3.02	71.73 ± 3.34
Fear	60.56 ± 4.28	72.08 ± 4.51	66.32 ± 2.78	66.34 ± 4.92	75.67 ± 4.97	71.00 ± 2.01
Anger	64.17 ± 5.16	70.00 ± 6.14	67.08 ± 3.55	65.24 ± 5.03	73.12 ± 4.23	69.18 ± 3.56
Surprise	68.11 ± 4.76	69.39 ± 3.34	68.75 ± 2.91	75.72 ± 4.34	75.84 ± 6.89	75.78 ± 2.44
Disgust	65.56 ± 6.32	68.19 ± 4.76	66.88 ± 3.60	64.78 ± 6.25	72.24 ± 3.56	68.51 ± 3.23

Table 3c
Percentage ± SD of classification of KNN and SVM classifiers with HOS features (M_{avg}, P_1, and P_2) between PD patients and healthy controls emotional state across *alpha* (8–13 Hz) frequency band.

Emotion	KNN classifier (%)			SVM classifier (%)		
	PD	HC	Average	PD	HC	Average
Happiness	74.72 ± 6.76	77.78 ± 3.52	76.25 ± 4.18	86.97 ± 6.82	88.56 ± 4.43	87.77 ± 3.11
Sadness	74.03 ± 2.62	80.97 ± 3.76	77.50 ± 2.56	79.85 ± 2.32	84.00 ± 3.33	81.93 ± 2.45
Fear	71.94 ± 4.80	78.50 ± 5.35	75.22 ± 3.24	78.45 ± 4.50	82.65 ± 4.05	80.55 ± 3.76
Anger	77.36 ± 3.76	82.64 ± 3.47	80.00 ± 2.53	78.56 ± 3.00	83.67 ± 2.92	81.12 ± 2.67
Surprise	79.47 ± 5.43	80.83 ± 2.71	80.15 ± 3.73	81.85 ± 5.56	83.23 ± 5.24	82.54 ± 4.45
Disgust	72.78 ± 5.56	79.53 ± 2.73	76.16 ± 2.93	75.56 ± 5.11	82.96 ± 3.78	79.26 ± 3.40

Table 3d
Percentage ± SD of classification of KNN and SVM classifiers with HOS features (M_{avg}, P_1, and P_2) between PD patients and healthy controls emotional state across *beta* (3–30 Hz) frequency band.

Emotion	KNN classifier (%)			SVM classifier (%)		
	PD	HC	Average	PD	HC	Average
Happiness	87.00 ± 2.55	88.01 ± 3.41	87.50 ± 2.23	90.89 ± 5.74	92.45 ± 5.95	91.67 ± 3.23
Sadness	80.87 ± 3.22	89.96 ± 2.36	85.41 ± 2.18	82.71 ± 6.62	90.91 ± 3.79	86.81 ± 5.56
Fear	81.94 ± 5.67	87.49 ± 3.82	84.72 ± 3.63	81.67 ± 4.34	89.78 ± 5.56	85.73 ± 4.33
Anger	81.03 ± 2.81	87.00 ± 4.90	84.02 ± 2.65	82.76 ± 3.77	89.47 ± 5.23	86.11 ± 3.43
Surprise	86.61 ± 3.52	87.02 ± 2.88	86.81 ± 2.44	91.65 ± 5.78	92.67 ± 3.88	91.67 ± 4.22
Disgust	81.82 ± 3.43	87.65 ± 3.65	84.73 ± 2.22	80.83 ± 4.34	89.92 ± 4.82	85.38 ± 3.56

Table 3e
Percentage ± SD of classification of KNN and SVM classifiers with HOS features (M_{avg}, P_1, and P_2) between PD patients and healthy controls emotional state across *gamma* (30–49 Hz) frequency band.

Emotion	KNN classifier (%)			SVM classifier (%)		
	PD	HC	Average	PD	HC	Average
Happiness	85.85 ± 2.89	90.27 ± 4.10	88.06 ± 3.39	86.68 ± 3.37	93.58 ± 3.55	90.13 ± 2.35
Sadness	78.87 ± 2.48	90.29 ± 3.49	84.58 ± 4.25	82.27 ± 2.48	91.09 ± 2.01	86.68 ± 1.04
Fear	80.32 ± 3.10	89.20 ± 4.90	84.76 ± 2.77	77.67 ± 4.28	92.76 ± 2.43	85.21 ± 3.88
Anger	77.29 ± 1.59	90.84 ± 4.12	84.06 ± 3.49	80.76 ± 2.51	90.13 ± 3.38	85.44 ± 2.57
Surprise	87.36 ± 3.29	88.98 ± 3.17	88.17 ± 4.10	92.27 ± 3.83	93.98 ± 4.00	93.12 ± 1.25
Disgust	78.96 ± 4.17	88.05 ± 2.75	83.50 ± 5.29	78.00 ± 3.59	91.97 ± 2.18	84.98 ± 2.58

and ALL bands using KNN and SVM classifier. From tables, several important observations can be drawn, for all the cases studied. First, it can be noted that the classification performance of HOS based features across ALL frequency bands is better than those based on individual frequency bands in both the groups. Second, it is found that the classification performance of alpha, beta, and gamma is obviously better than those of delta and theta bands in discriminating the emotional state EEG between PD patients compared to HC. This result partly reflects that higher frequency bands play a more important role in emotion activities than lower frequency

Table 3f
Percentage $\pm$ SD of classification of KNN and SVM classifiers with HOS features (M_{avg}, P_1, and P_2) between PD patients and healthy controls emotional state across *ALL* (combination of five bands) frequency bands.

Emotion	KNN classifier (%)			SVM classifier (%)		
	PD	HC	Average	PD	HC	Average
Happiness	85.90 ± 1.37	91.39 ± 3.28	88.64 ± 4.12	86.89 ± 1.74	94.76 ± 2.28	90.82 ± 2.37
Sadness	78.98 ± 3.37	91.78 ± 2.45	85.38 ± 3.77	82.56 ± 2.09	93.86 ± 3.92	88.21 ± 3.85
Fear	81.61 ± 4.23	90.49 ± 3.78	86.05 ± 4.29	79.99 ± 3.48	91.74 ± 1.38	85.85 ± 4.88
Anger	76.90 ± 3.19	93.28 ± 4.98	85.09 ± 2.48	80.98 ± 5.28	90.86 ± 2.48	85.92 ± 2.47
Surprise	88.20 ± 4.00	89.78 ± 2.10	88.99 ± 3.67	91.27 ± 4.04	94.98 ± 3.84	93.16 ± 3.19
Disgust	76.30 ± 3.15	92.39 ± 3.10	84.34 ± 4.29	80.57 ± 3.38	93.39 ± 2.97	86.98 ± 2.56

bands [63–65]. The current finding matches our previous study, where bispectrum emotion-specific features were mainly related to higher frequency band rather than lower frequency band in distinguishing six emotional states (happiness, sadness, fear, anger, surprise, and disgust) of PD patients and HC respectively with an averaged recognition rate of 70.10% ± 2.83% and 77.29% ± 1.73% [55]. These clearly suggest that EEG signals, being an activity of CNS, can reflect the underlying inherent emotional state of PD patients.

Third, PD patients achieved less classification performance for negative emotions (sadness, fear, anger and disgust), whereas classification performance for happiness and surprise emotion was comparable between PD patients and HC. This suggests that the results from PD patients with lower accuracy are those where EEG features are not reflecting the emotions, which can be interpreted as impairment in the brain processing of emotions, particularly for negative emotions. Recent evidence points to neuropathological changes in PD in many brain areas which are assumed to play key roles in emotion processing [66]. These include limbic structures such as the amygdala, and the ventral striatum, which is centrally located within the basal ganglia's limbic loop. Furthermore, our results are comparable with the more general hypothesis that a loss of complexity appears when the biological systems become functionality impaired [67,68].

Finally, the average classification performance of SVM out performs KNN classifier. For PD patients, the classification accuracy of HOS features across ALL frequency bands using SVM under each emotional state was: 86.89% ± 1.74% for happiness, 82.56% ± 2.09% for sadness, 79.99% ± 3.48% for fear, 80.98% ± 5.28% for anger, 91.27% ± 4.04% for surprise, and 80.57% ± 3.38% for disgust. For healthy controls, the classification accuracy of HOS features across ALL frequency bands using SVM under each emotional state was: 94.76% ± 2.28% for happiness, 93.86% ± 3.92% for sadness, 91.74% ± 1.38% for fear, 90.86% ± 2.48% for anger, 94.98% ± 3.84% for surprise and 93.39% ± 2.97% for disgust. This definitely proves the robustness of the SVM over KNN classifier for these datasets. Furthermore, this study provided a different viewpoint and new insights into emotional responses to PD patients. So far, no related work that specifically attempted the EEG frequency band based emotion classification in PD patients using machine learning techniques has been reported in the literature and therefore, it was difficult for the acquired results to be compared.

Some limitations of our study should be pointed out. First, the use of small number of PD samples which can affect the reliability of the system. Future studies should use larger number of PD patients to examine the relationship between brain activity and emotions. Second, the present study was limited by the fact that the PD sample consisted of PD patients in H&Y 1–3 stage, only, and all patients had ON-medication UPDRS motor scores mean value of 17.05. Thus, our finding is limited by the fact that persons with severe PD were not included in the study (H&Y 4–5 stage). Further research would explore this limitation. Finally, all PD patients were under dopamine replacement therapy, which might also affect the performance in the emotion processing [69] and future research is

required with unmedicated patients to reveal the actual effects on PD [70].

5. Conclusion

This study indicates that EEG signals are reliable in identifying the inherent emotional state of PD patients. The design of data acquisition protocol for eliciting the six emotional states (happiness, sadness, fear, anger, surprise and disgust) and the data acquisition methodology were explained in detail. Since the EEG signal is non-linear, non-stationary, and non-Gaussian in nature, non-linear features such as bispectrum were used to classify each of the six emotional states difference between PD and HC. The performance of the extracted features was analyzed using two classifiers namely KNN and SVM. Experimental results demonstrate that classification performance of bispectrum features across ALL frequency bands was better than those based on individual frequency bands in both the groups using SVM classifier. We also found that high frequency bands play a more important role in emotion activities than low frequency band. PD patients showed emotional impairments than HC, as demonstrated by a lower classification performance, particularly for negative emotions. Quantitative measure to assess emotional states may have a wide range of clinical applications in patient populations, including expression training, assessment of treatment effects and detection of persons at risk.

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